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DECISION ANALYSIS AS AN ELEMENT IN AN OPERATIONAL DECISION AID--ETC(U)

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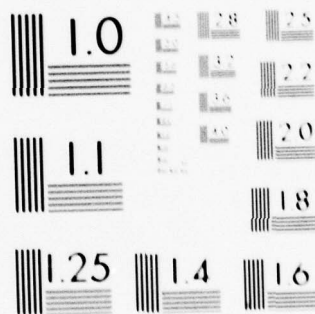
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April 1979

**FINAL TECHNICAL REPORT PR 78-29-6**

# **Decision Analysis as an Element in an Operational Decision Aiding System**

**PHASE V**

Scott Barclay  
Cameron R. Peterson  
L. Scott Randall  
Michael L. Donnell



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FINAL TECHNICAL REPORT PR 78-29-6

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# DECISION ANALYSIS AS AN ELEMENT IN AN OPERATIONAL DECISION AIDING SYSTEM (Phase V)

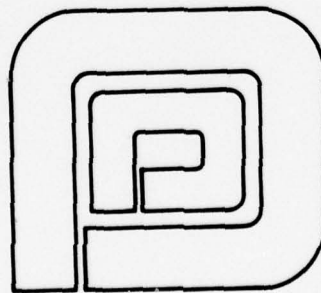
by

Scott Barclay, Cameron R. Peterson, L. Scott Randall and Michael L. Donnell

Sponsored by

Operational Decision Aids Project  
Office of Naval Research (Code 455)  
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April 1979



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Decision Aids	Analytic Modules											
Nonindependence	Multiple Uncertainty											
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) <p>△ This report describes PHase V efforts in the continuing investigation of the theoretical foundations of the decision-analytic model developed for the Office of Naval Research's Operational Decision Aiding Project. The principal issue under consideration was the degree to which the utilization of an incomplete, simple hierarchical model in the Tactical Decision Aid (TACAID) could lead to errors in inference as compared with a more complex Bayesian hierarchical model. Specifically, the more complex model would</p>												

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It was concluded that

be designed to make allowances for data dependencies as well as non-stationarity in enemy intent. The conclusion was drawn that a simple model can lead to significant and potentially costly errors in inference, and It was concluded that TACAID should be modified to handle these additional complexities. However, concurrent with such modifications, training in the proper utilization of the more complex TACAID would be mandatory to ensure proper utilization of the additional capabilities. As part of the current research and development effort, a situation definition capability, called TACDEF, was implemented for TACAID.

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## SUMMARY

This report presents the status and findings of the fifth phase (FY78) of research undertaken by Decisions and Designs, Incorporated (DDI) in support of the Office of Naval Research (ONR) Operational Decision Aids (ODA) Project. The goal of the ODA research program is the design and specification of a comprehensive decision-aiding subsystem (employing interactive man-machine information processing and analytical procedures) as a principal component of an operational command and control system.

Under four previous contracts with ONR, DDI has investigated the theoretical underpinnings of a Tactical Decision Aid (TACAID) and has constructed a prototype which is currently in a demonstration mode at the Project testbed. TACAID is in a computer-graphic form and is designed to cope with uncertainty by employing probabilistic inference and multiple value criteria. (See Peterson et al., 1977; Peterson et al., 1976; Brown et al., 1975; Brown et al., 1974.)

This year's efforts focused primarily upon a determination of the worth of adding a more complex Bayesian hierarchical inference (BHI) capability to the TACAID. This BHI capability would include specific provision for handling data dependencies, in the form of both redundancy and facilitation, and nonstationarity of the true hypothesis with regard to enemy intent. A situation definition capability for TACAID (labeled TACDEF) was also implemented.

### Research Achievements

The general conclusion of the research conducted during this year was that the addition of more complex modeling



features to TACAID would be well worth the necessary effort, with the caveat that care (in the form of training and a users' handbook) be taken to ensure proper utilization of these new capabilities. The sequence of research findings progressed as follows:

1. The exact effect that redundancy and facilitation could have on the probabilities relating data to hypothesis was explicitly formulated.
2. It was undertaken to simplify an already complex decision model (the Korean I&W model) for the purpose of comparing the two. Such simplification, while uncovering numerous dependencies of the redundant type, failed to uncover dependencies of the facilitative type, and this approach to comparing a simple with a complex model was abandoned.
3. It was shown that adding complexity to a simple single-stage Bayesian model (like that currently in TACAID) in the form of an intervening variable could account for both redundancy and facilitation.
4. The ONRODA situation was analyzed to determine the degree of facilitation and/or redundancy inherent in it. This involved the formulation of intervening variables which took the form of scenarios. The new hierarchical model was a highly facilitative one compared with the original, nonindependent model.
5. An artificially independent model was created to demonstrate that the correct, complex BHI model

took into account redundancy as well as facilitation. This model yielded probabilities of attack much higher than the correct model. It "jumped to conclusions" too rapidly.

6. To deduce the importance of the error in probability estimation made by the incorrect, artificially independent model, a computer simulation was performed. The simulation, using results of a particular data sequence in the ONRODA scenario, showed that drastic costs can be generated by treating data as independent when they are in fact dependent.
7. It remained to demonstrate the generality of the finding that a failure to explicitly take into account data dependencies could produce large and costly errors in probability estimation. It was demonstrated that in abstract but realistic situations involving intervening variables, complete redundancy and complete facilitation were obtainable.
8. The final theoretical question concerned the effect which a failure to handle nonstationarities in enemy intent could have on the diagnosticity of data and subsequent probability estimation. It was demonstrated that very small probabilities of change for the true hypothesis could significantly dilute the diagnosticity of typically highly diagnostic data.

## Conclusion and Recommendation

The above-cited research findings demonstrated conclusively that the assumption of independence among data and stationarity of enemy intent can lead to serious errors in probability estimates of enemy intent. TACAID should be expanded to include the capabilities to model data dependencies and nonstationarity of intent. However, any such augmentation of TACAID modeling capabilities should be accompanied by careful and thorough training of potential users to ensure that the new capabilities are thoroughly understood and properly utilized.

# CONTENTS

	<u>Page</u>
DD FORM 1473	ii
SUMMARY	iv
FIGURES	x
TABLES	xii
1.0 INTRODUCTION	1
1.1 Situation Assessment Investigation	1
1.2 Situation Definition Capability	3
2.0 AN EVALUATION OF THE VALUE OF INCORPORATING A MORE COMPLEX BAYESIAN HIERARCHICAL INFERENCE COMPONENT IN THE TACTICAL DECISION AID	5
2.1 Redundancy and Facilitation Using a Bayesian Hierarchical Structure	5
2.2 Initial Strategies for the Comparison of a Simple and a Complex Bayesian Hierarchical Inference Model	8
2.2.1 Simplifying a complex model	8
2.2.2 Adding complexity to a simple model	9
2.2.3 Conclusions drawn for adding complexity to a simple model	12
2.3 The Use of the ONRODA Situation to Measure the Cost of Assessing No Data Dependencies	12
2.3.1 A determination of the degree of facilitation and/or redundancy present in the ONRODA situation	12
2.3.2 Capturing dependencies in the ONRODA situation with a Bayesian hierarchical model	13
2.3.3 Measuring redundancy in the complex Bayesian hierarchical model	21
2.4 Computer Simulation of ONRODA Scenarios	23



	<u>Page</u>
2.5 Demonstrating the Generality of the Finding that High Costs are Generated by Treating Dependent Data as Independent	32
3.0 THE TREATMENT OF NONSTATIONARITY IN THE TACTICAL DECISION AID	36
4.0 TACAID SOFTWARE ENHANCEMENTS	41
4.1 Implementation of A Situation Definition Capability for TACAID	41
4.2 Installation of TACAID Enhancements in Project Testbed	43
5.0 CONCLUSION AND RECOMMENDATION	46
FOOTNOTES	47
REFERENCES	49
DISTRIBUTION LIST	50

## FIGURES

<u>Figure</u>		<u>Page</u>
2-1	CONDITIONAL PROBABILITIES LINKING TWO DATA, D1 AND D2, TO EACH OF TWO HYPOTHESES, H1 AND H2	6
2-2	D1 AND D2 INDEPENDENT	7
2-3	D1 AND D2 REDUNDANT	7
2-4	D1 AND D2 FACILITATIVE	7
2-5	REDUNDANCY PRODUCED BY AN INTERVENING VARIABLE	10
2-6	FACILITATION PRODUCED BY AN INTERVENING VARIABLE	11
2-7	CUMULATIVE EFFECT OF DATA ON INDEPENDENT BAYESIAN MODEL	15
2-8	CUMULATIVE EFFECT OF DATA RECEIVED ON THE INDEPENDENT BAYESIAN MODEL AND THE HIERARCHICAL MODEL	20
2-9	CUMULATIVE EFFECT OF DATA ON ALL THREE MODELS	24
2-10	SCORES FROM SIMULATION FOR HIERARCHICAL AND NONHIERARCHICAL MODELS	27
2-11a	PROBABILITY DATA FROM SIMULATION FOR THE HIERARCHICAL MODEL	28
2-11b	PROBABILITY DATA FROM SIMULATION FOR THE ARTIFICIALLY INDEPENDENT MODEL	29
2-12a	PROBABILITY DATA FROM SIMULATION FOR THE HIERARCHICAL MODEL BROKEN OUT BY ENEMY INTENTS	30
2-12b	PROBABILITY DATA FROM SIMULATION FOR THE ARTIFICIALLY INDEPENDENT MODEL BROKEN OUT BY ENEMY INTENTS	31
2-13	TOTAL REDUNDANCY PRODUCED BY AN INTERVENING VARIABLE	33

<u>Figure</u>		<u>Page</u>
2-14	TOTAL FACILITATION PRODUCED BY AN INTERVENING VARIABLE	35
3-1	THE EFFECT ON $P(H_1)$ OF VARIOUS PROBABILITIES OF CHANGE FOR THE TRUE HYPOTHESIS	38
3-2	SEQUENCES OF POSTERIOR PROBABILITIES MODIFIED TO TAKE INTO ACCOUNT PROBABILITIES FOR CHANGE FOR THE TRUE HYPOTHESIS	39
4-1	SPECIFICATION OF EVENT, ACTION, AND CRITERIA NAMES	42
4-2	CHECKLIST SPECIFICATION	42
4-3	SPECIFICATION OF INDICATORS AND LIKELIHOODS	44
4-4	SPECIFICATION OF CRITERIA WEIGHTS AND ACTION-EVENT VALUES	45

## TABLES

<u>Table</u>		<u>Page</u>
2-1	PROBABILITY OF DATA GIVEN HYPOTHESES FOR THE INDEPENDENT BAYESIAN MODEL	14
2-2a	PROBABILITY OF DATA GIVEN SCENARIOS	17
2-2b	PROBABILITY OF SCENARIOS GIVEN HYPOTHESES FOR THE HIERARCHICAL MODEL	19
2-3	PROBABILITY OF DATA GIVEN HYPOTHESES FOR THE ARTIFICIALLY INDEPENDENT BAYESIAN MODEL	22

DECISION ANALYSIS AS AN ELEMENT  
IN AN OPERATIONAL DECISION AIDING SYSTEM  
PHASE V

1.0 INTRODUCTION

During the past year (Phase V), the scope and objectives of the Operational Decision Aids (ODA) Project have remained constant, as in previous years. Thus, Decisions and Designs, Inc. (DDI), has centered its research and development efforts during this phase largely on the refinement and implementation of earlier concepts. Two categories of research and development effort were undertaken in support of decision aid design and prototype implementation: (1) an investigation to determine the value of implementing a more complex Bayesian hierarchical inference component of TACAID in its present form; and (2) a software enhancement of TACAID to provide a situation definition capability.

1.1 Situation Assessment Investigation

In applying any model to a real decision situation, certain assumptions must be made. For example, in structuring probability diagrams, events are extended into the future only up to some decision horizon. Similarly, in multi-attribute utility analysis, a manageable number of relatively important dimensions is often used rather than all dimensions. In short, it is always possible to model a situation in more detail than can be handled practically, and the art of decision analysis and the corresponding decision aid design specification include setting the appropriate level of detail.

In the Tactical Decision Aid (TACAID), two interrelated but different assumptions were made with respect to the



probability portion of the decision model. The first assumption was a stationarity assumption. That is, it was assumed that the identity of the true hypothesis would not change during the scenario. This means, for example, that if the enemy intended to attack at the beginning of the scenario, he would not change his mind and bluff. The second assumption was an independence assumption. That is, the impact of the receipt of each item of information was assumed to be independent of the receipt of all other data. This means, for example, that the detection of a missile radar on an enemy submarine would have exactly the same impact on the hypotheses whether or not prior communication had been detected between the submarine and a reconnaissance aircraft.

These assumptions, like all assumptions in a model, must be wrong at a fine enough level of detail. If the model is applied to a nonstationary environment, for example, the stationarity assumption might result in the TACAID probability bug moving toward one hypothesis as data favor that hypothesis, and then, as data begin to favor another hypothesis, becoming "trapped" so that overwhelming amounts of data favoring the other hypothesis would be required to move it toward the correct hypothesis. Similarly, treating data which are, in fact, dependent as independent may cause a series of relatively undiagnostic data to confirm one of the hypotheses at a level of certainty which is not appropriate. In fact, in a model which allows dependencies among data, the impact of a collection of information may be either greater or less than the sum of its parts.

It is necessarily the case that a complex model can be better (that is, a more precise predictor) than a simple model, and a simple model better than no model at all. This must be true if only because a complex model can include the simple model as a special case, and a simple model includes the case of "no model." The real question is how much

improvement over a simple model can be obtained with a complex model. If the simple model and the complex model were equally easy to implement, then one should always use the complex model. However, the complex model (that is, a model which includes both nonstationarity and nonindependence) requires many more assessments. Thus, the decision to use a more complex model rests on whether the improvement in performance, if any, is worth the increase in the number of assessments and the increased difficulty in structuring the model.

DDI has evaluated the increase in predictive accuracy which results from replacing a simple Bayesian hierarchical model with a more complex Bayesian hierarchical model. This improvement was first evaluated by using the ONRODA scenario as a special case. The improvement was then evaluated by using a statistical experiment, that is, a simulation experiment in which statistical commanders were presented with a number of scenarios and made decisions according to pre-programmed decision models. After a large number of such decision sequences, the performance of each of the decision models was measured, and the relative degradation in performance of proceeding from the complex model to an artificially independent model (see Section 2.3.3) was evaluated. DDI has also evaluated the effect of allowing for nonstationarity in a hierarchical inference model, and this work is described in Section 3.0.

## 1.2 Situation Definition Capability

Prior to this point in its development, TACAID has been applied to a tactical situation in a mini-scenario characterized by the presence of an enemy bomber and submarine in the vicinity of the Blue Task Force as it carries out the naval mission defined in the ONRODA scenario. Of course, to be truly versatile, TACAID must be able to offer decision-making assistance to the task force commander in a wide



variety of tactical situations, including the tactical threat thus far employed for demonstration.

In fact, the TACAID software and its underlying methodology contain the generality required to permit its use over a broad range of situations. None of the parameters associated with a specific situation--actions, events, indicators, criteria, likelihoods, probabilities, and so forth--are embedded within or constrained by the current implementation. All such quantities are considered by the TACAID software to be variables which are assigned values during an initialization process that occurs when TACAID execution begins. The initialization process currently retrieves these values from disc files generated by the "user" through use of a text editor. Creating these files with a text editor requires explicit knowledge of which files contain what information and in what format, something a typical user could not be expected to know. Nonetheless, the TACAID is inherently general in its implementation and possesses the potential for employment over a range of tactical situations.

To exploit this general-purpose nature of TACAID required that the aid be provided with an adjunctive "situation definition capability" to allow the user to specify situation parameters in a high-level, interactive manner and then to select situation definitions for analysis by the aid as a scenario develops. Such capability insulates the user from the details of TACAID implementation and permits him to apply its methodology to a variety of tactical decision problems. In this context, DDI has designed and implemented a situation definition capability to be compatible and consistent with the flexible, interactive nature of the TACAID. Explicit knowledge of which files contain what information and in what format is no longer required. Section 4.0 contains a more complete description of this new TACAID situation definition capability.

## 2.0 AN EVALUATION OF THE VALUE OF INCORPORATING A MORE COMPLEX BAYESIAN HIERARCHICAL INFERENCE COMPONENT IN THE TACTICAL DECISION AID

The principal efforts in the current project were devoted to determining the degree to which probabilistic models which assume that the probabilities of various data are independent can successfully be used in the place of models which incorporate dependencies among the data.

### 2.1 Redundancy and Facilitation Using a Bayesian Hierarchical Structure

Two main types of dependency were investigated, redundancy and facilitation. For example, consider the case in which there are two pieces of data relevant to a hypothesis; and, for simplicity, assume that the two are equally relevant to that hypothesis. Each of them has a 0.60 chance of being observed if Hypothesis 1 is true, and a 0.30 chance of being observed if Hypothesis 2 is true (see Figure 2-1). Now, if these two pieces of data contribute independently to the probability distribution over the two hypotheses, then, if one of them is observed and the other is not, the probability that Hypothesis 1 is true (given equal priors) is 0.53.<sup>1</sup> If neither datum is observed, the odds are 3 to 1 in favor of Hypothesis 2, and, if both of them are observed, the odds are 4 to 1 in favor of Hypothesis 1 (see Figure 2-2).

However, imagine the following hypothetical case: If one datum is observed but not the other, the probability in favor of Hypothesis 1 remains 0.53; and, in the event that neither datum is observed, the odds in favor of Hypothesis 2

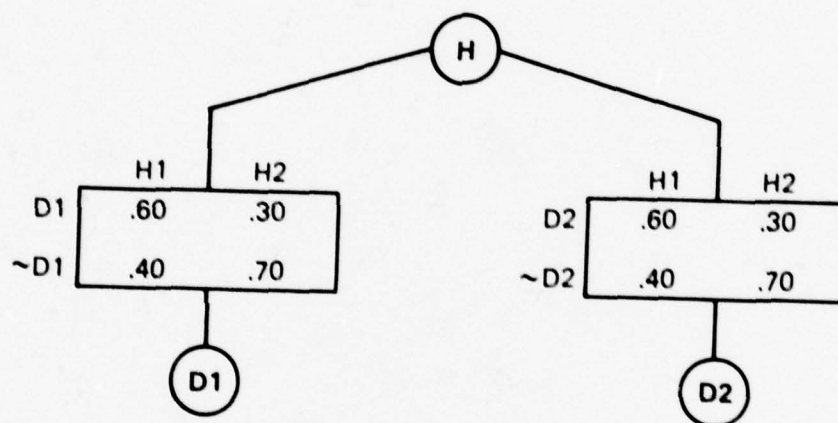


Figure 2-1  
 CONDITIONAL PROBABILITIES LINKING TWO DATA,  
 D1 AND D2, TO EACH OF TWO HYPOTHESES, H1 AND H2

	H1	H2
D1 ~D2	.53	.47
~D1 D2	.53	.47
~D1 ~D2	.25	.75
D1 D2	.80	.20

Figure 2-2  
D1 AND D2 INDEPENDENT

	H1	H2
D1 ~D2	.53	.47
~D1 D2	.53	.47
~D1 ~D2	.25	.75
D1 D2	.70	.30

Figure 2-3  
D1 AND D2 REDUNDANT

	H1	H2
D1 ~D2	.53	.47
~D1 D2	.53	.47
~D1 ~D2	.25	.75
D1 D2	.90	.10

Figure 2-4  
D1 AND D2 FACILITATIVE



remains 3 to 1, but if both data are observed the probability in favor of Hypothesis 1 is 0.70 instead of 0.80 (see Figure 2-3). In this case the two data would be said to be redundant.

Conversely, imagine that the probabilities remain the same in the first three cases, but that if both data are observed, the probability in favor of Hypothesis 1 becomes 0.90 instead of 0.80 (see Figure 2-4). In this case the data would be said to be facilitative.

Any models used to investigate the value of the added complexity of dependent data must include both redundant and facilitative dependencies.

## 2.2 Initial Strategies for the Comparison of a Simple and a Complex Bayesian Hierarchical Inference Model

The proposed effort called for a comparison to be made between a simple model and a complex model. There were two obvious ways in which to do this: either take a simple model and make it more complex, or simplify a complex model. The latter initially appeared to be the easier approach to adopt, since simplifying an already accurate and complex model would not require additional expert judgment. Conditional probabilities can be replaced everywhere by using their expected values as unconditional probabilities.

2.2.1 Simplifying a complex model - On the basis of meetings with Captain Robert E. Ammann, USN, Retired, DDI felt the Korean I&W model would be a suitable complex model for which to attempt simplification. This model was already complete: it was realistic (that is, it was a representative example of real situations); and it contained several levels

in the hierarchy. The model contained many instances of dependencies of the redundancy type, where several data confirm an intermediate level variable rather than impacting on the hypotheses directly. However, no dependencies of the facilitative type, where the impact of multiple data is more diagnostic than would be expected from their individual impacts, were found. For these reasons, the Korean I&W model was rejected as a complex model to be simplified. Instead, the modification of a simple model was undertaken with the hope that it would incorporate both kinds of dependencies.

2.2.2 Adding complexity to a simple model - The TACAID probability model is functionally a single-stage Bayesian model. Although the likelihood ratios for each datum are calculated by using two stages, they impact the probability distribution over the hypotheses independently. One way to provide for dependency among the data in this model would be to assess the likelihood distributions for various combinations of data. This means that in general the probability of datum  $D_1$  given the hypothesis  $H_1$  will be different if datum  $D_2$  has been observed than if it has not. The trouble with this method of dealing with dependencies is that, while it produces the correct numbers mathematically, it sheds little light on the reasons for the dependencies.

Another technique commonly used to handle dependencies of the redundant type is to create an intervening variable between two partially redundant data (see Figure 2-5).<sup>2</sup> In this method the reason for the redundancy is explicitly shown. The data are diagnostic of a state which is only partially relevant to the hypotheses. However, it is also the case that an intervening variable can produce the effect of facilitation between two data (see Figure 2-6).

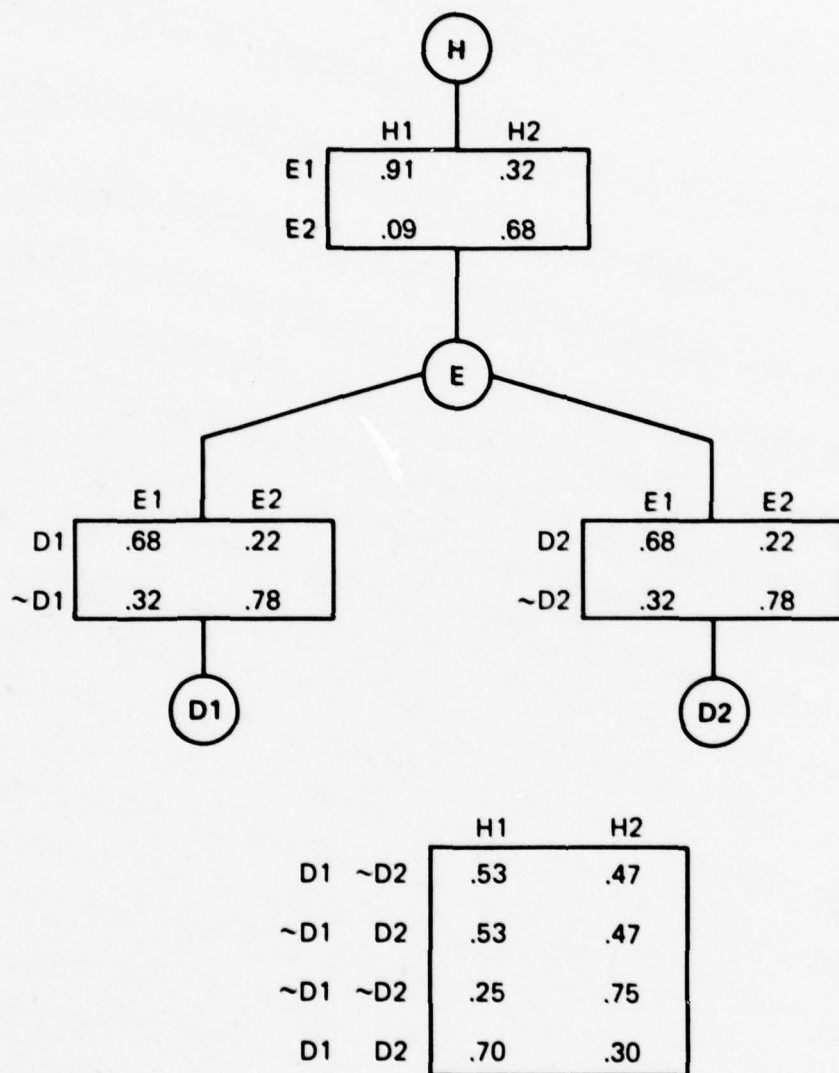


Figure 2-5  
REDUNDANCY PRODUCED BY AN INTERVENING VARIABLE



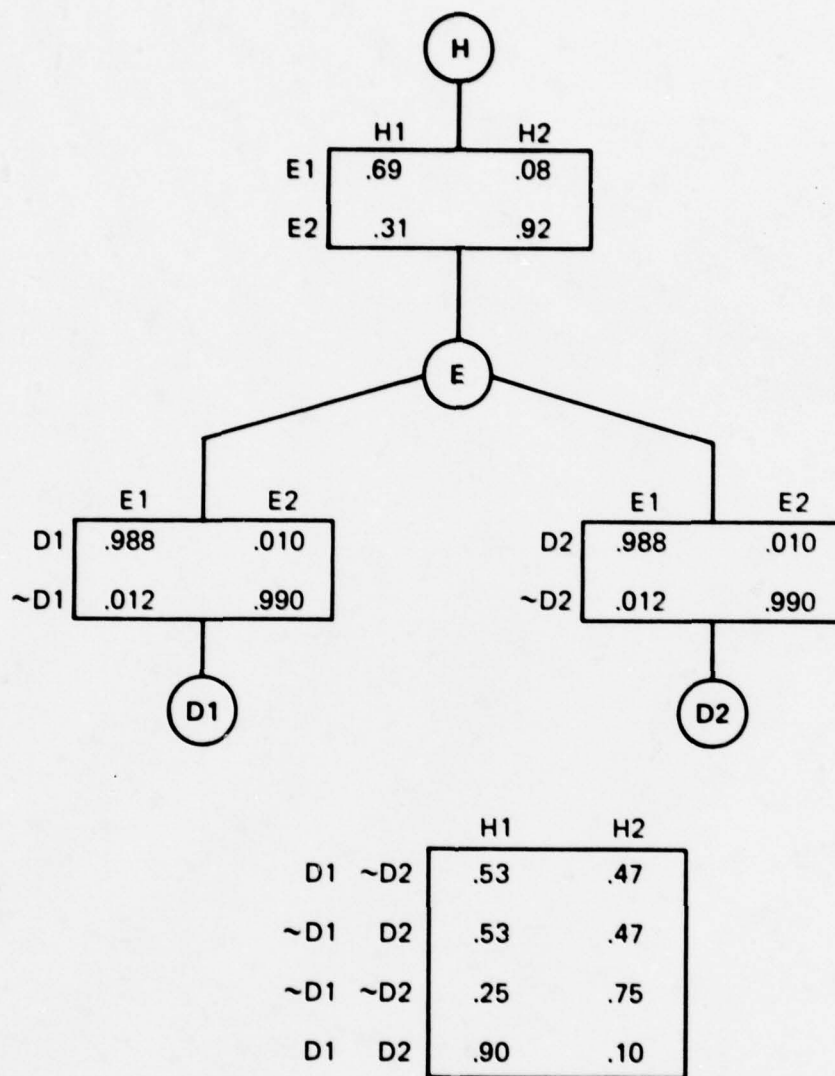


Figure 2-6  
FACILITATION PRODUCED BY AN INTERVENING VARIABLE

2.2.3 Conclusions drawn for adding complexity to a simple model - It is possible to model both facilitative and redundant kinds of dependencies by using a hierarchical structure and conditionally independent likelihoods. This suggests that when building Bayesian hierarchical models, the decision analyst should attempt to build in facilitation and redundancy by focusing the expert's attention on packages of data (or intervening variables) which interact to produce more or less diagnosticity jointly than would be expected from their individual diagnosticities. With this method of modelling, a hierarchical structure was created for the TACAID scenario which included both facilitative and redundant types of dependencies but did not require the assessment of conditionally dependent likelihoods.

2.3 The Use of the ONRODA Situation to Measure the Cost of Assessing No Data Dependencies

Having demonstrated that it was possible to model facilitative as well as redundant dependencies with a Bayesian hierarchical model, research efforts turned to using ONRODA scenarios to measure the cost of assuming no data dependencies.

2.3.1 A determination of the degree of facilitation and/or redundancy present in the ONRODA situation - The first step in investigating the effects of data dependencies on the Bayesian model was to discover the degree of facilitation and/or redundancy present in the situation represented by the Tactical Decision Aid, but not captured by the independent Bayesian model. During an interactive session with the Aid, Captain Ammann isolated a sequence of nine indicators from the list of potential indicators he believed most likely to contain dependencies among the data. The nine data items consisted of "search," "track," "targeting,"

"beacon test," "guidance radar," "data link," "command comms," "launch sounds," and "intercept" (see Table 2-1). In fact, Captain Ammann felt that these data were facilitative; that is, the data acted together to make the decision maker more sure that the enemy intended to attack than he would be if they acted independently.

As a baseline, the impacts of each of the nine data elements were plotted as a function of their arrival in the sequence (see Figure 2-7). This graph shows the effect on the likelihood of attack as each datum is added to those already received. The likelihood rises progressively until it ultimately exceeds 99% with the receipt of the "intercept" datum. Note that the data generally do not cause very large jumps in the cumulative probability, with the exception of datum 3, "targeting," which has a likelihood ratio of 8 to 5, and datum 8, "launch sounds," with a likelihood ratio of 12 to 1. This profile reflects the phenomenon perceived earlier by Captain Ammann that the TACAID probability bug appeared to stay relatively stationary during the arrival of several data, and then suddenly jumped toward attack when it was too late for effective action to be taken.

2.3.2 Capturing dependencies in the ONRODA situation with a Bayesian hierarchical model - To capture any dependencies which might be present, the simple Bayesian model was restructured using a new intermediate node to create a Bayesian hierarchical model, as described in Section 2.2. The hierarchical model was constructed using the expertise of Admiral William Shawcross. He was familiar with the situation represented in the current decision aid, the assessed probabilities contained in it, and the reasoning which led to their current values.

	S U R V E I L	B L U F F	A T T A C K
SEARCH	.300	.810	.860
TRACK	.460	.670	.680
TARGETING	.070	.150	.240
BEACON TEST	.050	.570	.600
GUIDANCE RADAR	.050	.620	.650
DATA LINK	.050	.670	.700
COMMAND COMS	.050	.570	.600
LAUNCH SOUNDS	.050	.050	.600
INTERCEPT	.100	.100	.700

Table 2-1  
 PROBABILITY OF DATA GIVEN HYPOTHESES  
 FOR THE INDEPENDENT BAYESIAN MODEL

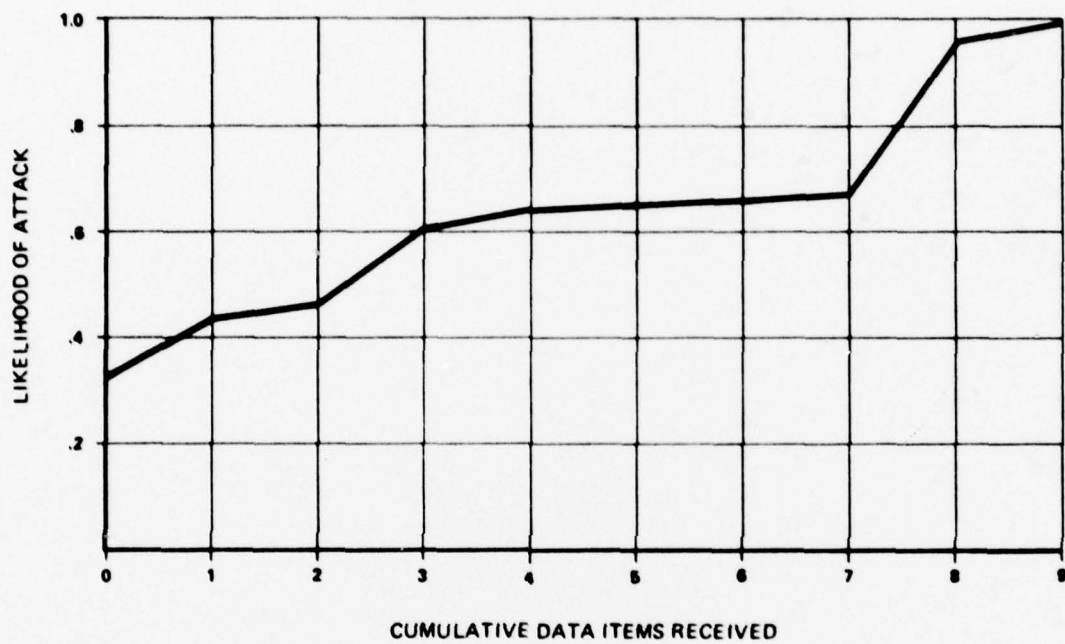


Figure 2-7  
CUMULATIVE EFFECT OF DATA ON INDEPENDENT BAYESIAN MODEL



After an iterative process, a hierarchical structure was settled upon which seemed to capture the essence of the situation. It was decided that the most helpful intermediate node would be one which represented "scenarios." That is, the bluff or intended attack of the enemy might take place via various action scenarios, and the specification of these scenarios should make the assessment of the probabilities for the various data items easier.

Admiral Shawcross felt that there was really only one scenario for surveillance, and only one way that the enemy could carry out an attack if attacking were his intent. That is, the particular factors assumed to be true in the TACAID situation precluded the use of other surveillance or attack scenarios. However, there were a variety of bluffs that the enemy might employ. The most straightforward way of dealing with these bluffs was to postulate that all bluffs would mimic the attack sequence, but that each bluff sequence would have a different point at which the attack sequence was broken off. These sequences, differing in length, were labeled Bluff 1, Bluff 2, and so forth. They included all possible lengths of sequence except those sequences which included the data items "launch sounds" or "intercept." These data were not considered permissible elements of any bluff scenario.

Using this relatively simple scheme, the probability of occurrence of each of the possible data was assessed given that the enemy was using scenario 1, 2, 3, and so forth. These probabilities are given in Table 2-2a. Thus it was judged that if the enemy intended merely to conduct surveillance, there was only a 15% chance that he would use his radar in search mode (because he would prefer to use passive means of surveillance), a 30% chance that he would fly a track appropriate for attack, a 10% chance that he would engage in targeting, and so on. Notice that these

	S U R V E I L	B L U F F 1	B L U F F 2	B L U F F 3	B L U F F 4	B L U F F 5	B L U F F 6	B L U F F 7	A T T A C K
SEARCH	.150	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TRACK	.300	.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
TARGETING	.100	.000	.000	1.000	1.000	1.000	1.000	1.000	1.000
BEACON TEST	.050	.000	.000	.000	1.000	1.000	1.000	1.000	1.000
GUIDANCE RADAR	.050	.000	.000	.000	.000	1.000	1.000	1.000	1.000
DATA LINK	.010	.000	.000	.000	.000	.000	1.000	1.000	1.000
COMMAND COMMS	.050	.000	.000	.000	.000	.000	.000	1.000	1.000
LAUNCH SOUNDS	.000	.000	.000	.000	.000	.000	.000	.000	1.000
INTERCEPT	.000	.000	.000	.000	.000	.000	.000	.000	1.000

Table 2-2a  
PROBABILITY OF DATA GIVEN SCENARIOS



events are neither mutually exclusive nor exhaustive, and therefore the probabilities do not sum to 100%. If the enemy intends to bluff, then, depending on which type of bluff he intends to use, various sequences of data would be seen. For example, if he intends to bluff by using bluff sequence 3, it is certain that he will use search, will fly the track, and will engage in targeting, since this constitutes the definition of bluff sequence 3. Finally, it was judged that in this situation there was only one way for an attack to take place; thus, if the enemy intends to attack, it is certain he will produce all of the data in the sequences.

The next step in the construction of the hierarchical model is to relate the nine scenarios to the three original hypotheses. This relation is shown in Table 2-2b. Because it was judged that surveillance and attack could only take place in one way, the columns for these hypotheses are simple and not very interesting. However, the middle column shows that if the enemy intends to bluff, it is most likely he will do so using bluff sequence 3, slightly less likely that he would use bluff sequences 4, 5, 6, or 7, a little less likely that he would use bluff sequence 2, and about half as likely that he would use bluff sequence 1. The reasoning behind these judgments was that the enemy needs to carry out the sequence to some extent for the bluff to be effective, but he is less likely to carry it into the beacon test, guidance radar, data link, or command comms states for fear that the bluff may provoke an attack by the blue forces.

When these data are processed one at a time with the hierarchical model, the likelihood of attack goes up more swiftly and smoothly than it did with the previous model (see the dashed line in Figure 2-8).<sup>3</sup> In fact, at the point when all the data through command comms have been

	S U R V E I L	B L U F F	A T T A C K
SURVEILLANCE	1.000	.000	.000
BLUFF 1	.000	.084	.000
BLUFF 2	.000	.143	.000
BLUFF 3	.000	.168	.000
BLUFF 4	.000	.151	.000
BLUFF 5	.000	.151	.000
BLUFF 6	.000	.151	.000
BLUFF 7	.000	.151	.000
ATTACK	.000	.000	1.000

Table 2-2b  
 PROBABILITY OF SCENARIOS GIVEN  
 HYPOTHESES FOR THE HIERARCHICAL MODEL

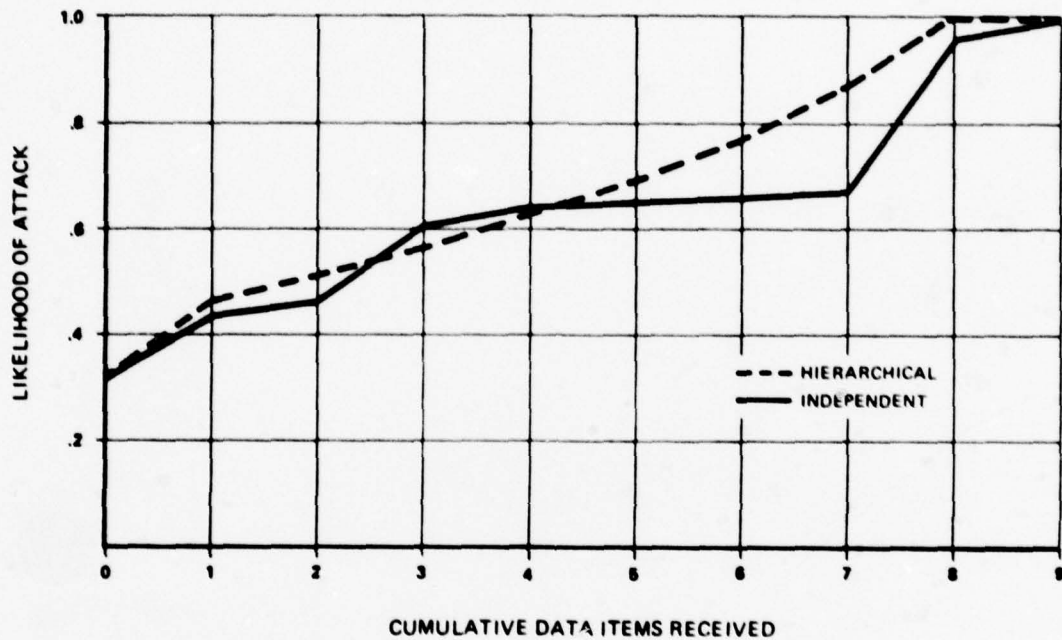


Figure 2-8  
CUMULATIVE EFFECT OF DATA RECEIVED ON THE  
INDEPENDENT BAYESIAN MODEL AND THE HIERARCHICAL MODEL

received, the hierarchical model produces a probability of attack of 0.87 while the independent Bayesian model produces a probability of only 0.68. Thus, it is clear that considerable facilitation is occurring in the Bayesian hierarchical model compared to the simpler independent Bayesian model. It is important to note that no attempt was made during the assessment process to cause the hierarchical model to be facilitative; instead, the technique of using an intermediate-level variable allowed the facilitation present in the expert's understanding of the situation to be revealed.

2.3.3 Measuring redundancy in the complex Bayesian hierarchical model - Although it may not be obvious, there is also considerable redundancy involved in the Bayesian hierarchical model. This is necessarily the case since multiple data impact the same scenarios. Thus, the probability that the enemy is using a particular scenario will often not be increased by the receipt of new information, although the information might serve to rule out a scenario.

To measure the degree of redundancy present in the hierarchical model, one can use the following technique: For each datum taken one at a time, compute the likelihood of that datum given each of the hypotheses. That is, compute the likelihood for each datum as mediated by the intervening variable. Table 2-3 contains the data likelihoods given each hypothesis calculated in this manner. These data likelihoods can now be combined in an artificial independent model, that is, combined as though they were in fact independent (this was done for the simple Bayesian model in Section 2.3.1). This technique will create artificially high likelihood ratios for each of the data because it incorporates all of the facilitation inherent in the hierarchical model but removes all the redundancy.



	S U R V E I L	B L U F F	A T T A C K
SEARCH	0.15	1	1
TRACK	0.3	0.91597	1
TARGETING	0.1	0.77311	1
BEACON TEST	0.05	0.60504	1
GUIDANCE RADAR	0.05	0.45378	1
DATA LINK	0.01	0.30252	1
COMMAND COMMS	0.05	0.15125	1
LAUNCH SOUNDS	0	0	1
INTERCEPT	0	0	1

Table 2-3  
 PROBABILITY OF DATA GIVEN HYPOTHESES  
 FOR THE ARTIFICIALLY INDEPENDENT BAYESIAN MODEL

The results of using this artificial independent model are shown by the dotted line in Figure 2-9. The probability of attack rises smoothly and even more swiftly than the line for the hierarchical model. For example, following the receipt of the first seven data, the probability of attack for the artificial independent model is 0.99, while the likelihood of attack for the hierarchical model is 0.87 and for the independent Bayesian model, 0.68. Thus there is, clearly, substantial redundancy in the hierarchical model (as compared to the artificial independent model) as well as facilitation (as compared to the original independent Bayesian model).

The above-described data dependencies were demonstrated among a particular set of data in a particular scenario, where the set of data was selected because of its presumed ability to exhibit strong interdependencies. It is therefore difficult to generalize these results to other situations. Consequently, this research was extended by investigating in more abstract situations the degree to which it was possible to manipulate the magnitude of the effects of data dependencies with the use of the Bayesian hierarchical model.

#### 2.4 Computer Simulation of ONRODA Scenarios

In the previous section, it was demonstrated that artificially treating dependent data in the ONRODA scenarios as if they were independent leads to a marked change in posterior probabilities. The results of this evaluation, displayed in Figure 2-9, showed that the nonhierarchical (artificially independent) model, which treated all data as independent, substantially overestimated the probability of attack as compared with the (correct) hierarchical model that incorporated all data dependencies. The amount of

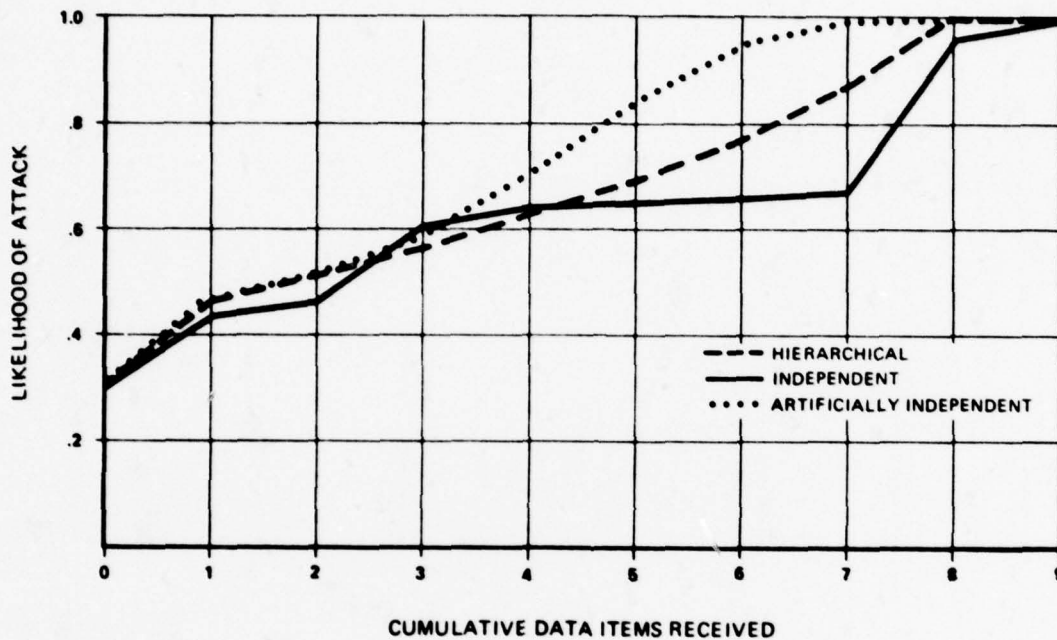


Figure 2-9  
CUMULATIVE EFFECT OF DATA ON ALL THREE MODELS

overestimation by the nonhierarchical model is fairly substantial as measured by the probabilities displayed in Figure 2-9. The next logical question concerns how important that probability difference would be in decision-making situations.

One way to measure this importance would be to construct a utility model which assigned values to the results of making the right and wrong inferences about the enemy intention. A model of this sort could, however, become quite cumbersome in a situation such as this which involves numerous scenarios. Furthermore, the fundamental question of whose utilities and importances should be used is a difficult one to answer. Another basic approach to measuring the importance of the difference between the predicted and actual probabilities would be to use a proper probability scoring rule. This approach was selected since it avoided further complicating an already complex situation.

To measure the importance of this difference in probabilities, a computer simulation was performed. This simulation created a statistical environment in which it was assumed that the hierarchical model was correct. Decision-making performance was simulated under two conditions: in the first it was assumed that the decision maker received the correct hierarchical probabilities as inputs, and in the second it was assumed that he received the incorrect non-hierarchical (artificially independent) probabilities that overestimated the probability of attack. The decision-making process was scored by using a proper probability scoring rule to generate a payoff matrix infinitely sensitive to differences in probability input. A logarithmic scoring rule was selected. One hundred data sequences were randomly generated and modeled hierarchically and independently.



Figure 2-10 displays the results of this simulation. Mean scores are plotted, except that scores of  $-\infty$  were discarded before calculating the mean. The scores have been rescaled so that they fall in the interval between 0 and 1.0 rather than between  $-\infty$  and 0. The score earned by probabilities generated by the hierarchical model began at a little over .2, went up to about .75, and then leveled off at about .5 toward the end of the data sequence. By comparison, the probabilities generated by the nonhierarchical model, which failed to incorporate the data dependencies, received the same score as the hierarchical model during the early stages in the sequence, but its scores then fell off very sharply and finally ended with the minimum possible score, near 0 for the last three data in the sequence.<sup>4</sup> The dashed line in Figure 2-10 represents the score which would have been obtained by a commander who ignored the data and continuously professed complete ignorance as to which hypothesis was correct. By using the nonhierarchical (artificially independent) model one would actually do worse than if he continuously professed complete ignorance!

Figures 2-11a,b and 2-12a,b depict more detailed data from the computer simulation. Figure 2-11a,b contains plots of the maximum probability of the correct hypothesis [ $P_{\text{MAX}}(C)$ ], the minimum probability of the correct hypothesis [ $P_{\text{MIN}}(C)$ ], the average probability of the correct hypothesis [ $P_{\text{AVG}}(C)$ ], and the probability corresponding to the average score [ $P(\text{SCORE}_{\text{AVG}})$ ] (with scores of  $-\infty$  discarded) for both the hierarchical and artificially independent models. Note that the latter curve dips below .33 for the hierarchical model but not for the independent model. The independent model has treated redundant data as independent and "jumped to conclusions" too rapidly. For completeness, Figure 2-12a,b presents the maximum, minimum, and average probabilities of inferring the correct hypotheses given each of the three possible enemy intents.

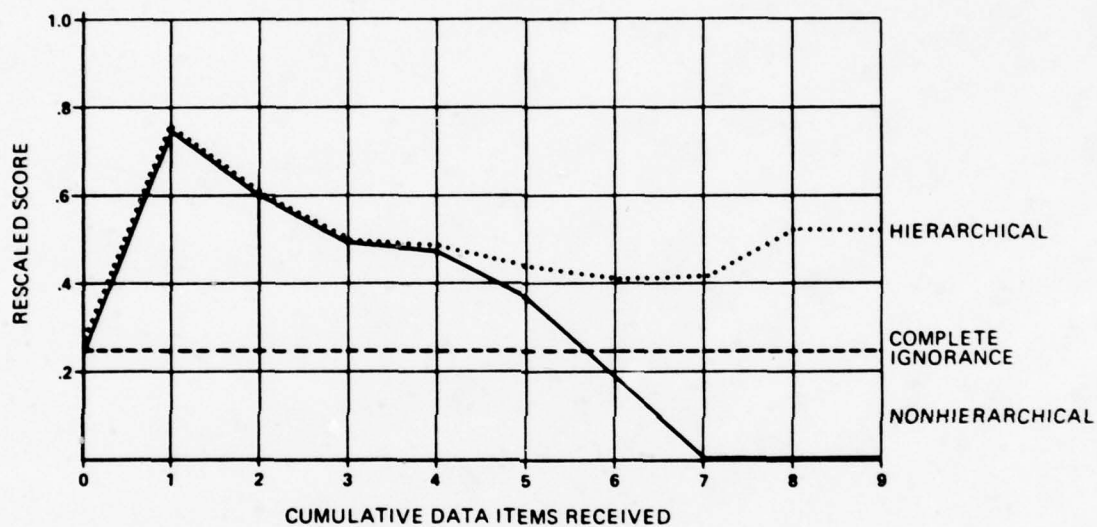


Figure 2-10  
SCORES FROM SIMULATION FOR  
HIERARCHICAL AND NONHIERARCHICAL MODELS

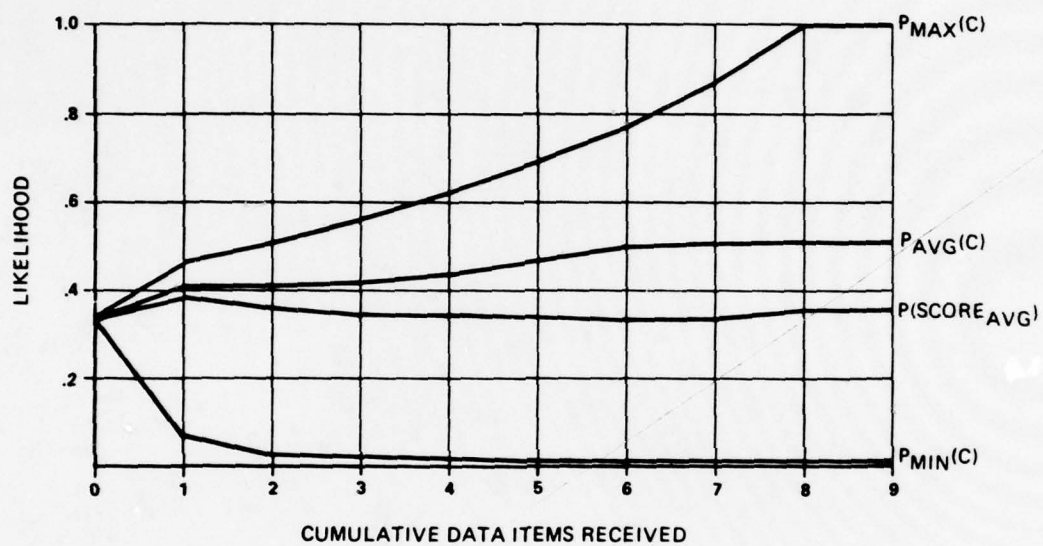


Figure 2-11a  
**PROBABILITY DATA FROM  
 SIMULATION FOR THE HIERARCHICAL MODEL**

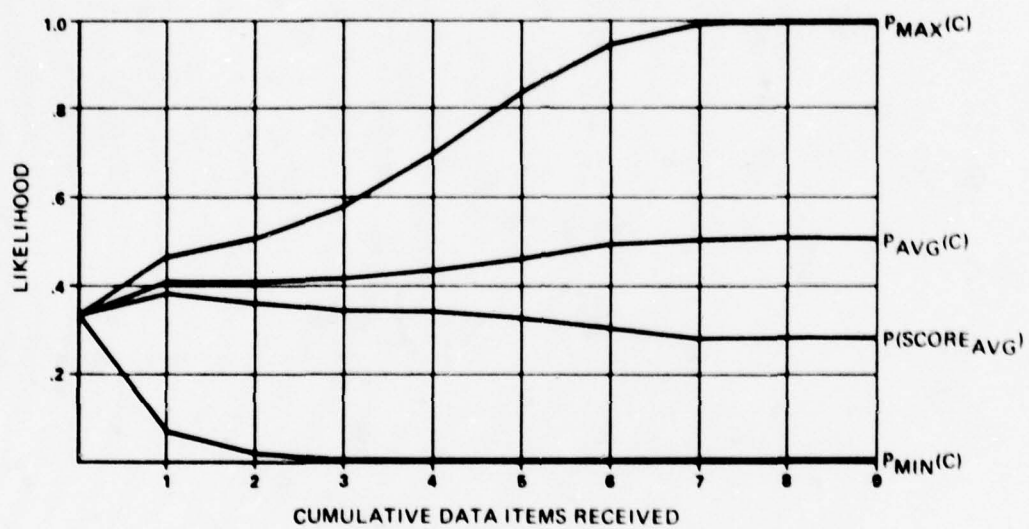


Figure 2-11b  
 PROBABILITY DATA FROM SIMULATION  
 FOR THE ARTIFICIALLY INDEPENDENT MODEL



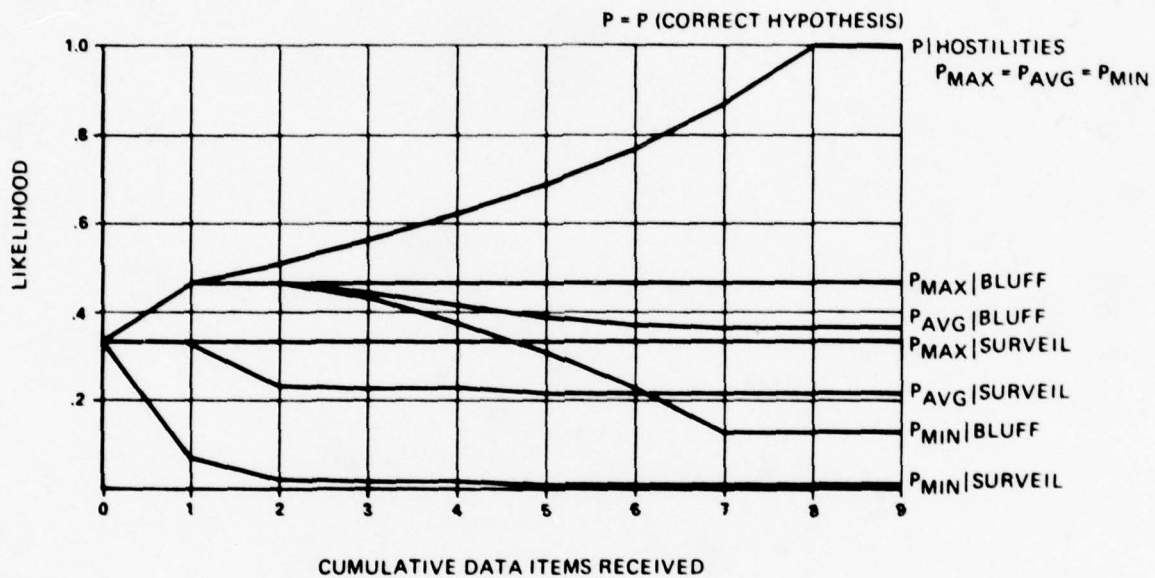


Figure 2-12a  
 PROBABILITY DATA FROM SIMULATION  
 FOR THE HIERARCHICAL MODEL BROKEN OUT BY ENEMY INTENTS

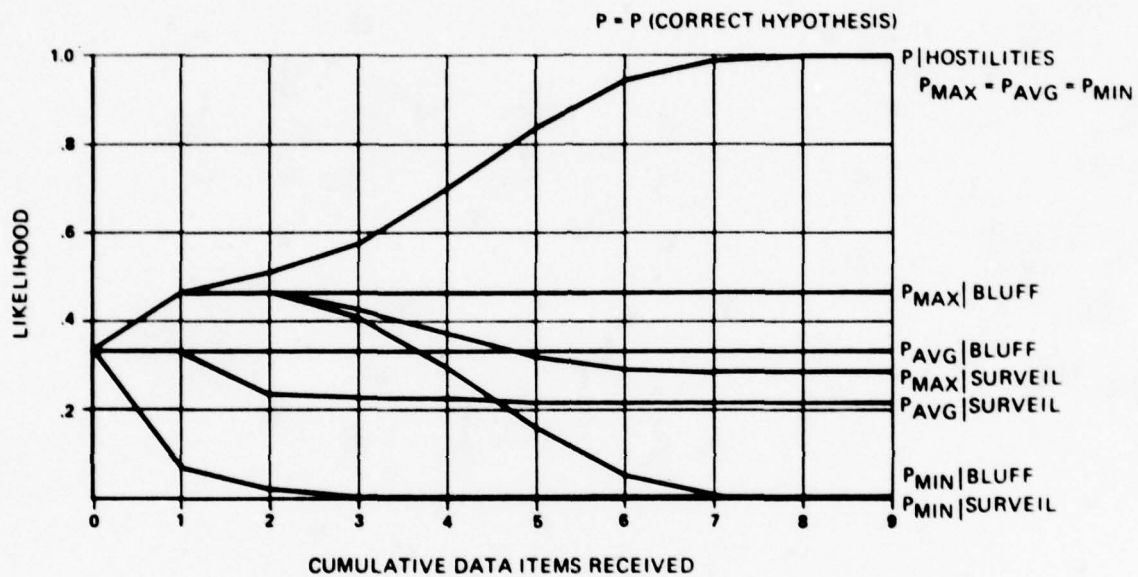


Figure 2-12b  
**PROBABILITY DATA FROM SIMULATION FOR THE  
 ARTIFICIALLY INDEPENDENT MODEL BROKEN OUT BY ENEMY INTENTS**

The simulation, using results of a particular data sequence in a particular scenario, shows that drastic costs are generated by treating data as independent when they are in fact dependent. The magnitude of the effect is large, but recall that this particular data sequence within the ONRODA scenario was selected because, on a priori grounds, it was judged to contain a large degree of data dependency. Thus, the demonstration by this simulation that a substantial cost could be attributed to ignoring data dependencies in a particular data sequence of a particular scenario has somewhat limited generality. In the next section it is demonstrated that high degrees of redundancy and facilitation are possible in not too unrealistic situations.

#### 2.5 Demonstrating the Generality of the Finding that High Costs are Generated by Treating Dependent Data as Independent

An obvious approach to the problem of generality would be to apply the simulation to the results of representative sets of data sequences and a representative set of possible scenarios. However, the task of constructing such data sequences and scenarios would be enormous. Consequently, the next task evaluated the possible range of effects of treating data dependencies in a hierarchical model as independent rather than dependent.

Recall that in Section 2.2, moderate degrees of both redundancy (see Figure 2-3) and facilitation (see Figure 2-4) were shown to be possible. Just how far can we carry this degree of redundancy and facilitation in the abstract? As far as we desire. Figure 2-13 demonstrates that for suitable choices of probabilities relating data to intervening variables and intervening variables to hypotheses, total redundancy is possible. That is, the mutual occurrence

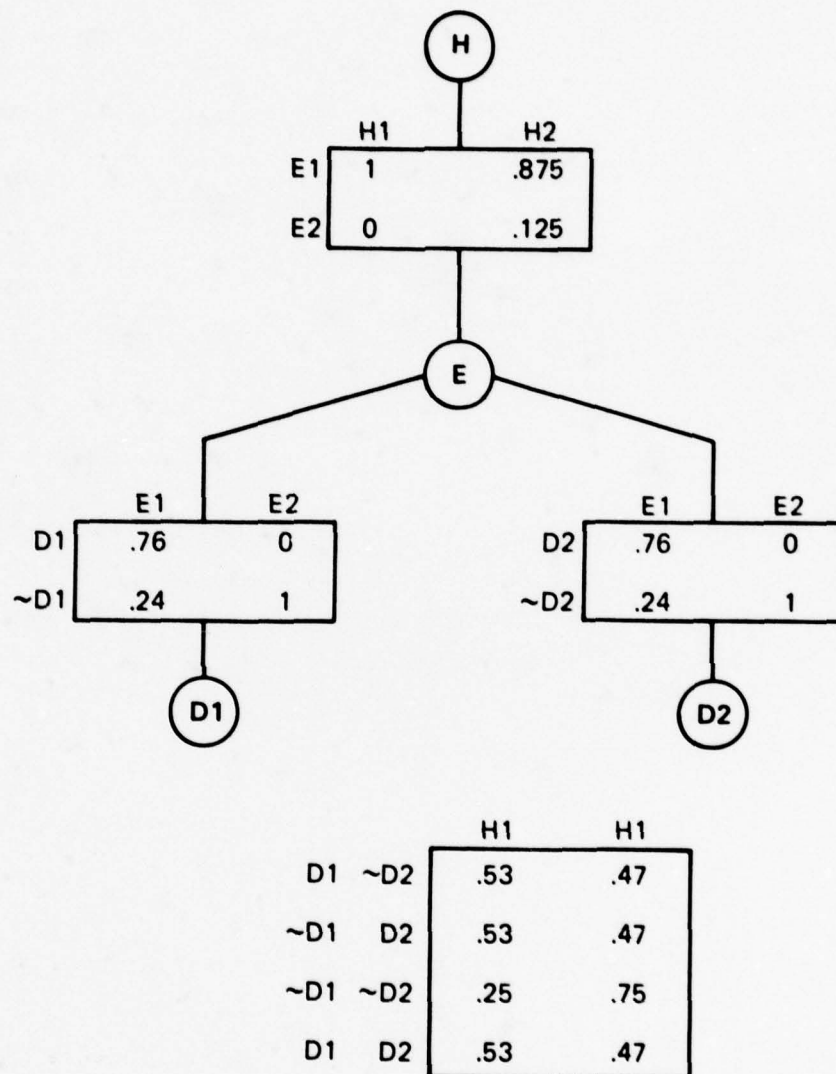


Figure 2-13  
TOTAL REDUNDANCY PRODUCED BY AN INTERVENING VARIABLE



of two data, both diagnostic of a single hypothesis, can potentially provide us with no more stronger evidence for that hypothesis than the unitary occurrence of either datum. Similarly, it can be shown that there exists a set of probabilities relating data, intervening variables, and hypotheses which exhibit total facilitation. Such a set of probabilities is illustrated in Figure 2-14.

Although the situations depicted in Figures 2-13 and 2-14 are purely abstract, it would not be too difficult a task to generate potential real-world scenarios for which those probabilities were realistic.

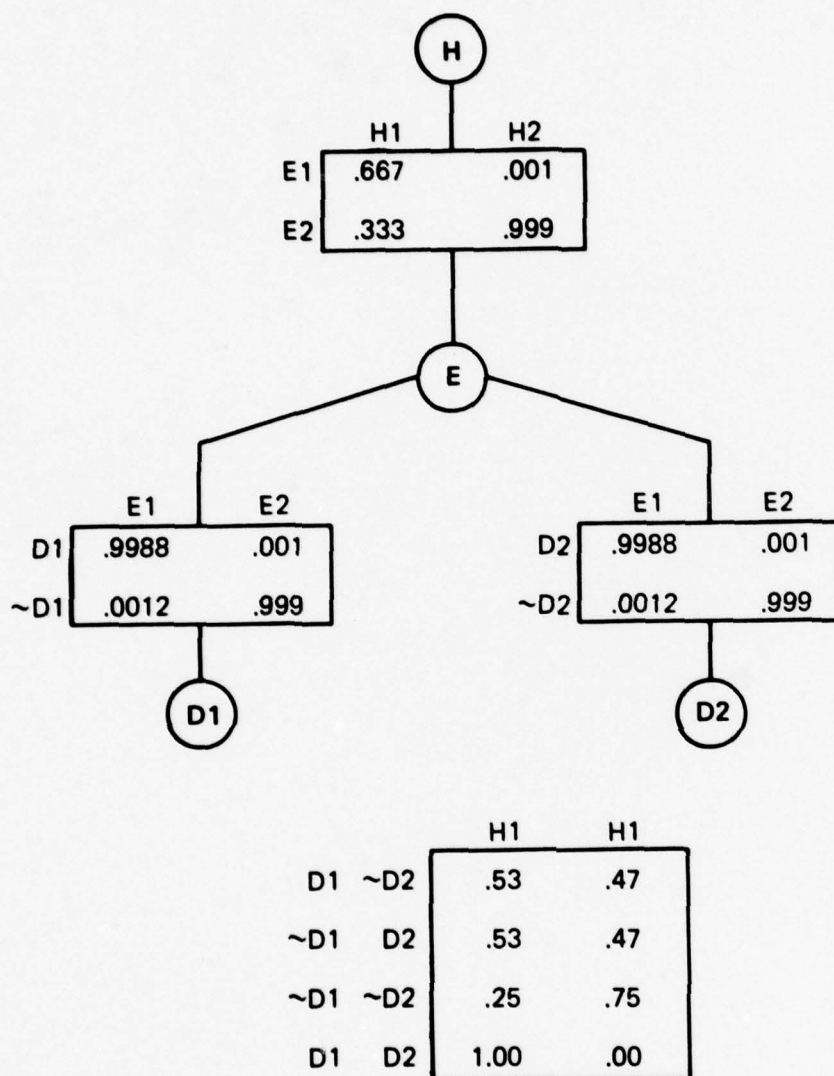


Figure 2-14  
TOTAL FACILITATION PRODUCED BY AN INTERVENING VARIABLE

### 3.0 THE TREATMENT OF NONSTATIONARITY IN THE TACTICAL DECISION AID

The final theoretical issue to be considered in this research concerned the effect of allowing for nonstationarity of enemy intent. The current version of TACAID assumes stationarity. That is, it is assumed that before embarking on a course of action, the enemy commander has decided exactly what he is doing, and he will not change his mind before fulfilling his intended objective. In reality the enemy commander may be highly likely to divert from his intended course of action due to events which could not be foreseen before embarking on that course of action.

With the currently implemented situation, numerous responsive actions by friendly forces could be postulated and interpreted as likely to deter the enemy commander from carrying through with his originally selected course of action. Bluff or surveillance action could become an attack if friendly response to either indicated that an attack could be successfully undertaken. Similarly, significant friendly force response to the initial events in an attack sequence could lead the enemy commander to revert to a sequence matching the surveillance or one of the bluff scenarios.

Rather than explicitly model the effect of nonstationarity within the ONRODA scenario, an approach was taken similar to that in the previous section. That is, it is sufficient to demonstrate that in hypothetical, yet reasonable, circumstances the effect of nonstationarity upon the probability of a given hypothesis can be quite dramatic.

First, assume that subsequent to the receipt of a datum of a certain diagnosticity, the probability of the most likely hypothesis of two alternative hypotheses ( $H_1$ ) is known. If the identity of the true hypothesis is known to be likely to change with probability  $p(C)$  after the receipt of that datum, then the revised probability of  $H_1$ , taking into account the probability of change is  $p(H_1)(1-p(C)) + (1-p(H_1))p(C)$ . Figure 3-1 exhibits revised values of  $p(H_1)$  given  $p(C)$  for various values of  $p(H_1)$ . From these lines it can be seen that  $p(C)$  can have a quite dramatic effect on  $p(H_1)$ .

Now, consider the following situation which, while still abstract, corresponds more closely in detail to the ONRODA situation. Assume that a choice is to be made between two hypotheses,  $H_1$  and  $H_2$ , that nine data are sequentially received, and that for each  $p(D|H_1) = .7$  and  $p(D|H_2) = .3$ . Furthermore, assume that prior to the receipt of any data,  $p(H_1) = p(H_2) = .5$ . Finally, assume that subsequent to the receipt of each datum, there is a constant, known probability of the identity of the true hypothesis changing. Figure 3-2 displays sequences of posterior probabilities, each revised to take into account various values of  $p(C)$ . The effect of rather small values of  $p(C)$  is to dilute dramatically the diagnosticity of the data, causing the plots of  $p(H_1)$  for  $p(C) > 0$  to asymptote at values significantly less than 1.0. A  $p(C)$  as small as .05 can cause  $p(H_1)$  to asymptote at .92. Note that if  $p(C) = .5$ , then one would do well to simply ignore all of the data since  $p(H_1)$  cannot exceed .5.

The above-cited results relate directly to the judgment by Gettys et al. (1976) that the DDI prototype decision aid



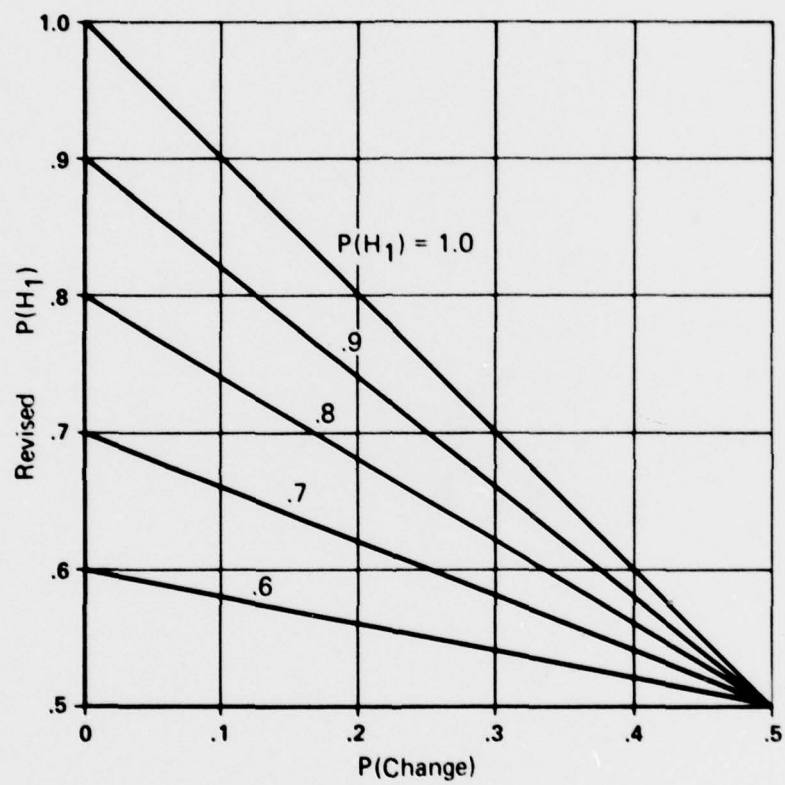


Figure 3-1  
THE EFFECT ON  $P(H_1)$  OF VARIOUS  
PROBABILITIES OF CHANGE FOR THE TRUE HYPOTHESIS

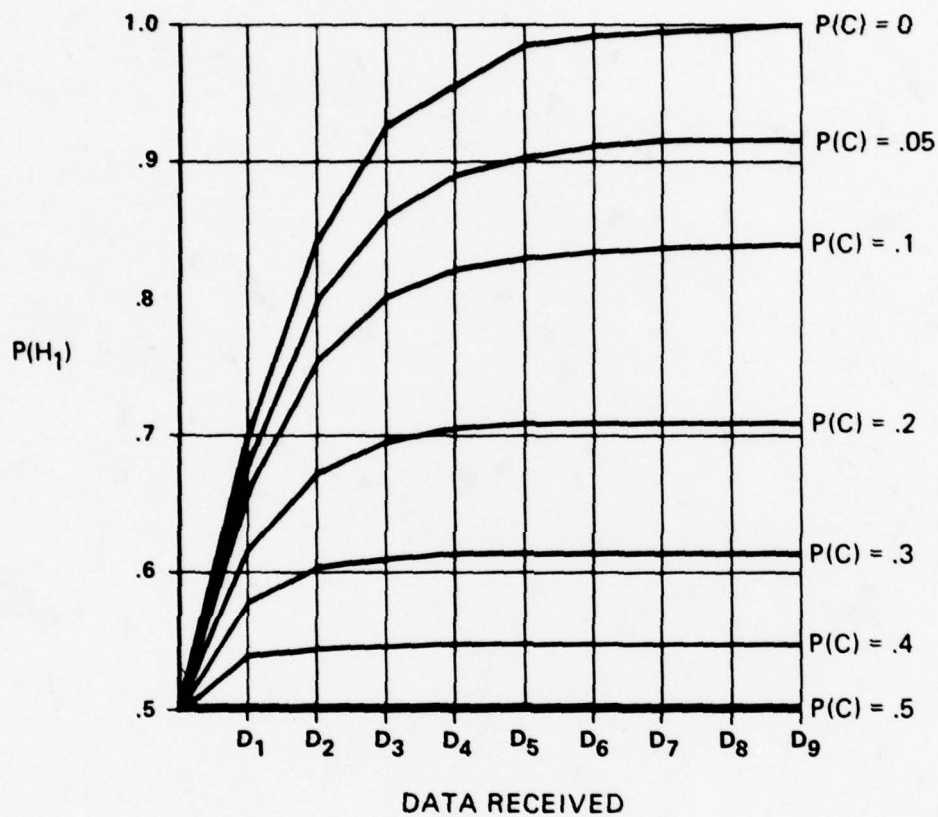


Figure 3-2  
SEQUENCES OF POSTERIOR PROBABILITIES MODIFIED  
TO TAKE INTO ACCOUNT PROBABILITIES OF CHANGE FOR THE TRUE HYPOTHESIS

should allow for an assessment of the probability that the enemy has changed his intent instead of assuming that all the data observed comes from a steady generation state. The effect of nonstationarity of enemy intent has been systematically examined, and it has been demonstrated that an allowance for the assessment of the probability of change in enemy intent after the receipt of each datum will alleviate the problem of the "trapped bug"--the failure of the system's indication of the existing tactical situation to be congruent with the perceptions of users.

It must be emphasized, however, that when properly utilized, the aid is not likely to encounter a "trapped-bug" problem. The aid is designed more for use in a stationary environment than a nonstationary one. The aid should be turned on when the potential threat or a set of circumstances indicating the possible existence of a threat is apparent. At that point, the aid helps to analyze more fully the threat situation. The practice of turning the aid on when a vessel embarks and constantly feeding it data based upon periodic samples from its environment is not a good one and will surely lead to the "trapping of the bug."

## 4.0 TACAID SOFTWARE ENHANCEMENTS

### 4.1 Implementation of A Situation Definition Capability for TACAID

The TACAID Definition Module, TACDEF, enables the user to define models to be processed by TACAID. The user can specify events, actions, indicators, evaluation criteria, event prior probabilities, indicator likelihoods, and action-event values for the various criteria. Thus, he can analyze any problem of his choosing which lends itself to the framework of the TACAID methodology.

Although TACAID has always possessed the capability to analyze user-defined problems, a generalized user-oriented definition module did not exist prior to implementation of TACDEF. TACDEF provides an interactive elicitation process using display images similar to those of TACAID. The elicitation process is decomposed into three phases to allow the user "escape" points at which he may interrupt model definition and then later resume.

During the first phase of the elicitation process, TACDEF asks the user to specify the number of actions and the number of criteria to be considered. (Because of the triangular format used by TACAID to represent probability space, the number of events is assumed always to be three.) TACDEF then asks the user to provide explicit and abbreviated event names, explicit and abbreviated action names, and criteria descriptors. These steps are shown in Figure 4-1. Next, TACDEF requests a "checklist" for each action, which will be displayed by TACAID whenever the probability bug lies within the triangle region associated with that action. An example of checklist specification appears in Figure 4-2. This completes the first phase of the elicitation process.



ENTER NUMBER OF ACTIONS DESIRED:  ENTER NUMBER OF CRITERIA DESIRED:

ENTER EXPLICIT EVENT NAME:	<input type="text" value="ROUTINE"/>	ENTER BRIEF EVENT NAME:	<input type="text" value="RTN"/>
ENTER EXPLICIT EVENT NAME:	<input type="text" value="BLUFF"/>	ENTER BRIEF EVENT NAME:	<input type="text" value="BLF"/>
ENTER EXPLICIT EVENT NAME:	<input type="text" value="ATTACK"/>	ENTER BRIEF EVENT NAME:	<input type="text" value="ATK"/>
ENTER EXPLICIT ACTION NAME:	<input type="text" value="ATTACK"/>	ENTER BRIEF ACTION NAME:	<input type="text" value="ATK"/>
ENTER EXPLICIT ACTION NAME:	<input type="text" value="DEFEND"/>	ENTER BRIEF ACTION NAME:	<input type="text" value="DFN"/>
ENTER CRITERION NAME:	<input type="text" value="MISSION EFFECTV"/>		
ENTER CRITERION NAME:	<input type="text" value="OWN FORCE DAMAG"/>		

Figure 4-1  
SPECIFICATION OF EVENT, ACTION, AND CRITERIA NAMES

ENTER CHECK LIST FOR ACTION " ATTACK ":

ATTACK:

- Flank speed.
- Launch attack aircraft.
- Alert recovery units.

Figure 4-2  
CHECKLIST SPECIFICATION

At this point, the user can either stop or proceed to one of the other two phases. Once the first definition phase has been completed, the user may elect to execute either of the other phases as often as necessary or desired.

The second phase of model definition begins with a request for event probabilities, followed by requests for indicator descriptions and associated likelihoods, as shown in Figure 4-3. At the end of this process, the user may elect to stop, to continue with the third phase, or to repeat the process again.

In the third phase of elicitation TACDEF requests criteria weights and action-event values, as shown in Figure 4-4. As with the other phases, the user can stop, continue with another phase, or repeat.

#### 4.2 Installation of TACAID Enhancements in Project Testbed

Under previous contract efforts, DDI assisted University of Pennsylvania personnel in converting a prototype version of the TACAID software from its implementation for a Vector General graphic display system to the Project testbed Ramtek graphic display system. Following that conversion effort, DDI implemented several functional enhancements for the TACAID on the Vector General system.

Under the contract covered by this report, DDI provided to testbed personnel machine-readable copies of the source code changes resulting from these enhancements. In addition, DDI personnel provided on-site advisory assistance to testbed personnel to facilitate incorporation of the changes into the Ramtek version of the TACAID software.

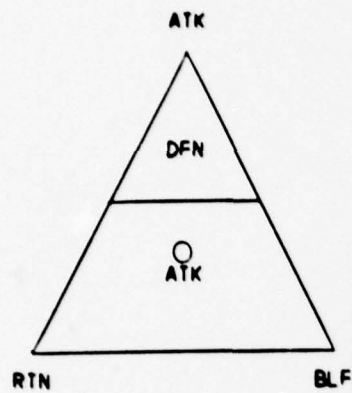
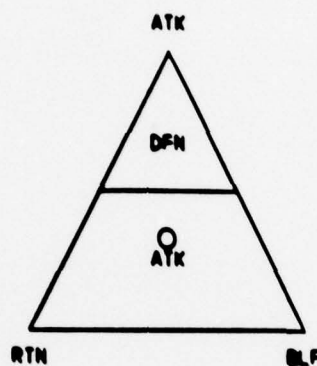
			LIKELIHOODS			PROBABILITIES		
INDICATORS	RECEIVED/HYPOTHEZED	DATE-TIME	ROUTINE	BLUFF	ATTACK	ROUTINE	BLUFF	ATTACK
PRIOR PROBABILITIES						34	33	33
SURVL ACTV--BEAR			30	95	90			
SURVL ACTV--NO BEAR			70	5	10			
OVERT PREP--YES			10	99	70			
OVERT PREP--NO			90	1	30			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
NULL			1	1	1			
ENTER INDICATOR NAME:	<input type="text"/>		<input type="text"/>			<input type="text"/>		
			UP			DOWN		

Figure 4-3  
SPECIFICATION OF INDICATORS AND LIKELIHOODS

EVENTS:	EXPECTED VALUE
ATTACK	70
DEFEND	20



ACTION INDICATOR  
LIKELIHOOD TABLE

EVENTS:	MISSION EFFECTV			OWN FORCE DAMAG		
	ROUTINE	BLUFF	ATTACK	ROUTINE	BLUFF	ATTACK
ATTACK	100	90	50	95	95	0
DEFEND	0	0	0	100	0	0
CRITERION WT	40			60		

ENTER NEW VALUE:

Figure 4-4  
SPECIFICATIONS OF CRITERIA WEIGHTS AND ACTION-EVENT VALUES



## 5.0 CONCLUSION AND RECOMMENDATION

The current research effort has sought to determine the error in estimation due to the substitution of a simple inference model for a more complex Bayesian Hierarchical Inference model and the cost to the user of such a substitution. The potential for serious error and high costs was demonstrated in the case of models which fail to take data dependencies and nonstationarity of hypotheses into account. Finally, a situation definition capability, TACDEF, has been fully implemented. This added feature should lead to fuller utilization of the TACAID.

The results indicate that it would be well worth undertaking the implementation of capabilities for handling data dependencies and nonstationarity in TACAID. Caution should be taken, however, to ensure that, if implemented, such additional features would be properly utilized. An incorrectly utilized complex tool is of less value to the decision maker than a simple, correctly utilized tool. The cost of implementing these additional features would be nothing in terms of computer hardware since ONR already has the appropriate hardware. However, computer software costs are not insignificant and would total approximately \$50,000. The cost of preparing a handbook with example models to be constructed, exercised, and recorded would be roughly equivalent to the computer software. This handbook would demonstrate the potential value to be gained from more complex Bayesian Hierarchical Inference models which the TACAID could accommodate. It should be written primarily for the benefit of analysts who might use the augmented TACAID and should not be written as a user's manual for the novice. Knowledgeable analysts using the augmented TACAID could, with the benefit of the handbook, structure and implement more complex BHI models with little more time and effort than is now required for simpler models.

# FOOTNOTES

1. The appropriate equation here is

$$p(H_1|D_1, \sim D_2) = \frac{p(D_1, \sim D_2|H_1)p(H_1)}{p(D_1, \sim D_2|H_1)p(H_1) + p(D_1, \sim D_2|H_2)p(H_2)}$$

2. One of the appropriate equations here is

$$p(H_1|D_1, D_2) = p(H_1|E_1)p(E_1|D_1, D_2) + p(H_1|E_2)p(E_2|D_1, D_2)$$

$$\begin{aligned} &= \left( \frac{p(E_1|H_1)p(H_1)}{p(E_1|H_1)p(H_1) + p(E_1|H_2)p(H_2)} \right) \\ &\times \left( \frac{p(D_1, D_2|E_1)p(E_1)}{p(D_1, D_2|E_1)p(E_1) + p(D_1, D_2|E_2)p(E_2)} \right) \\ &+ \left( \frac{p(E_2|H_1)p(H_1)}{p(E_2|H_1)p(H_1) + p(E_2|H_2)p(H_2)} \right) \\ &\times \left( \frac{p(D_1, D_2|E_2)p(E_2)}{p(D_1, D_2|E_2)p(E_2) + p(D_1, D_2|E_1)p(E_1)} \right) \end{aligned}$$

where  $p(E_1) = p(E_1|H_1)p(H_1) + p(E_1|H_2)p(H_2)$  and similarly for  $p(E_2)$ .

3. The equations here are similar but more complex than those given in the previous two footnotes. The reader is referred to Kelly and Barclay (1973) for their exact form.
4. The average scores for the correct hierarchical model do not approach 1.0 for data 8 and 9 because although the occurrence of data 8 and 9 ensure that the enemy is attacking (and the probability of attack immediately jumps to 1.0), the failure of data 8 and 9 to occur still leaves us making a potentially incorrect choice between the Surveillance scenario and the possible Bluff scenarios.

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Wayne, PA 19087

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